Screening of a Probabilistic Database Using Stochastic Reasoning Driven by Surrogate Models

A Case Study for Candidate Recognition for Waterflood Implementation in Oil Field Development Planning

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Abstract

Waterflooding is among the oldest and perhaps the most economical of oil recovery processes to extend field life and increase ultimate oil recovery from naturally depleting reservoirs. During waterflood operations, water is injected into the reservoir to maintain a certain reservoir pressure as well as to push the oil in the reservoir towards the producing wells. Nowadays, any organization always has to strive for lean and efficient technologies and processes to maximize profit also when looking deeper into their reservoir portfolios in order to identify additional waterflooding opportunities. Time and information constraints can limit the depth and rigor of such a screening evaluation. Time is reflected by the effort of screening a vast number of reservoirs for the applicability of implementing a waterflood, whereas information is reflected by the availability and quality of data (consistency of measured and modeled data with the inherent rules of a petroleum system) with which to extract significant knowledge necessary to make good development decisions.

A new approach to screening a large number of reservoirs uses a wide variety of input information and satisfies a number of constraints such as physical, financial, geopolitical, and human constraints. In a fully stochastic workflow that includes stochastic back-population of incomplete datasets, stochastic proxy models over time series, and stochastic ranking methods using Bayesian belief networks, more than 1,500 reservoirs were screened for additional recovery potential with waterflooding operations. The objective of the screening process is to reduce the number of reservoirs by one order of magnitude to about 100 potential candidates that are suitable for a more detailed evaluation. Numerical models were used to create response surfaces as surrogate reservoir models that capture the sensitivity and uncertainty of the influencing input parameters on the output. Reservoir uncertainties were combined with expert knowledge and environmental variables and were used as proxy model states in the formulation of objective functions. The input parameters were initiated and processed in a stochastic manner throughout the presented work. The output is represented by a ranking of potential waterflood candidates.

The benefit of this approach is the inclusion of a wide range of influencing parameters while at the same time speeding up the screening process without jeopardizing the quality of the results.

Keywords

Probabilistic Database; Screening; Querying; Proxy Modeling; Bayesian Belief Network; Self-organizing Maps; Clustering

Introduction

Chevron Nigeria Ltd. is successfully applying waterflooding to increase oil recovery in a limited number of reservoirs. Current waterfloods represent only ~25% of the risked oil-in-place volumes and ~3% of reservoirs. Field development plans, which estimate the ultimate recovery of each field, recognize that significant contingent resources associated with waterflooding may exist in over 1,500 reservoirs under primary depletion. A screening exercise over the entire reservoir portfolio was conducted to identify potential waterflood candidate reservoirs. The main challenges of screening exercises are usually the tight time frame that is imposed on the schedule and the limited manpower available as well as the recognition and management of uncertainties due to lack of data. A large number of reservoirs require a phased approach, with the analysis detail increasing in each phase to address the decision (FIG. 1).

The objective of Phase 1 is the evaluation of all reservoirs in the portfolio using only reservoir and field-level data to develop a ranked list of about 100

candidate reservoirs for waterflooding. As an important part of the decision-making process, the ranking exercise should integrate not only the reservoir's resource potential, but also environmental and operational considerations such as security, existing infrastructure, and economic feasibility.

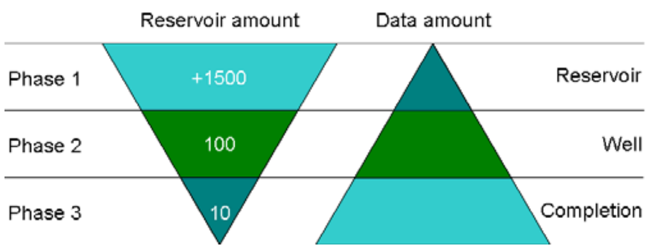

FIG. 1 SKETCH OF THE THREE-PHASED SCREENING APPROACH TO IDENTIFY RESERVOIR CANDIDATES FOR WATERFLOOD IMPLEMENTATION DEPICTING THE AMOUNT OF DATA AND RESOLUTION REQUIRED FOR EACH PHASE

Subsequent Phases will further reduce the number of potential reservoirs by one order of magnitude. Spatial and time-dependent data at the well level are included in a Phase 2 and analyzed with methods that provide appropriate accuracy in their prediction. Phase 3 evaluates data at the completion level and applies rigorous field development planning techniques to deliver probabilistic resource assessments, reservoir management strategies, and depletion plans. Operational considerations will remain as ranking factors through all three phases. Both the operational and reservoir assessments will provide data for investment decisions.

This paper describes Phase 1 of the screening exercise.

Workflow Overview

The workflow for the screening study consists of four main components. Firstly, the entire dataset is surveyed, and key parameters for the classification of reservoir types are identified. If data are obviously not consistent or missing, they are flagged to indicate potential problems. Severe conditions may exist for a database in which the amount of missing or inconsistent data is so high that a screening study is rendered incapable of delivering sensible results. As it can be seen in FIG. 2, which depicts the completeness of the study database, the viscosity value for oil is available for only fewer than 20% of all reservoirs. However, since the viscosity is one of the main parameters influencing the waterflood (Craig, 1971), a qualitative statement on the viability of water injection for more than 80% of all reservoirs is not possible. To overcome this database deficiency, the dataset is back-populated using multi-variant correlation techniques. In the second step, statistical analysis of clustered parameters and the identification of the inherent error of each data member are used to transfer both original and back-populated data to a probabilistic database, in which each data entry contains a mean value and a standard deviation. The completed dataset is mined for similarities using self-organizing maps (SOM) to classify all reservoirs into clusters based on the nonobvious and intrinsic properties of their key parameters.

The third step involves the construction of stochastic proxy models, response surface models (RSM) which are used to formulate the objective function, the difference in oil recovery between a development with and without water injection, and which allow qualitative conclusions on the recovery factor for each reservoir in both cases. Furthermore, environmental considerations and expert knowledge are captured in proxy models that define the economic and physical viability for waterflooding for individual reservoirs. The stochastic output of the viability proxies is used as states for the Bayesian belief network (BBN) in the fourth step and is combined with the differential recovery proxy to construct the objective function. The Bayesian network is used to calculate the joint probabilities for all proxies feeding into the objective function to evaluate the applicability for waterflood implementation for a specific reservoir. Based on the resulting probabilities, all reservoirs are ranked for the potential of success of waterflood implementation.

Back-population of Data

For the purposes of this paper, data can be divided into two categories: the base and derived parameters. The former is the observed data as measured in laboratories and in the field. The latter can be either calculated from the former or reflect states or conditions (such as "if–else" statements). It can be assumed that a relationship between some or all data exists in one way or the other. Correlatable data might be linked through empirical relationships like pressure/volume/temperature (PVT) data or are correlatable through physical or mathematical processes such as the sweep efficiency (i.e. how much oil is replaced by the injected water), recovery, and oil viscosity. There also are inherent relationships that can be observed. Examples of those are the linear relationship of temperature versus depth, the logarithmic relationship between permeability (and linear to porosity) versus depth, and a power law

relationship of reservoir size with depth (assuming that deeper formations were exposed longer to tectonic forces than shallower formations). However, nonlinear, multilayered, parallel regression techniques have been used in this paper to define the various more complex and less obvious relationships. The advantage of these methods is that all data can be considered simultaneously so that potentially even hidden or unobvious relationships are found (Pyle, 1999, Zangl, 2003). Moreover, a vast amount of data can be looked at in a minimum of time.

Probabilistic Databases

The introduction of statistical methods and uncertainty management in the workflow allows overcoming deficiencies related to incomplete datasets and guarantees meaningful screening over entire datasets (Graf et al. 2008). Rather than representing one world in deterministic databases, probabilistic databases capture multiple worlds and deliver a probabilistic answer to queries. The probabilistic appearance of the data members—in its simplest form an uncertainty distribution—allows managing the imprecision of data such as nonmatching data values, imprecise queries, inconsistent data, misaligned schemas, etc. (Dalvi and Suciu 2005). The statistical analysis of the relation of each data member and its error to expected and calculated value(s), or inherent errors such as from the measurement, can derive the distribution and the validity range for each data member. Incomplete data can be back-populated relationally with a distribution describing the amount of and the confidence in the available data for a specific data member. Moreover, relational data can be used to define the predictability of the data and introduce the inherent error. The database would then contain only probabilistic data. Measured data would normally have a higher confidence and back-populated data would have a larger uncertainty range (or standard deviation).

Screening of Probabilistic Data

An operation or the application of an algorithm on the probabilistic database results in a stochastic output, whose distributions reflect the uncertainties of the input parameters captured by the database. In contrast to screening using deterministic data, which are unambiguous in the ranking exercise, the screening of probabilistic data must consider the entire distribution and, hence the decision on the ranking must consider a multitude of factors such as mean values, the confidence levels, and the delimiting conditions. A probabilistic reasoning method deploying BBNs can be used as a screening algorithm to compute the probability of success for a particular objective function.

Database Construction and Reconstruction

The project database contained more than 100 different data members, some of which are depicted in FIG. 2. However, initially only a subset of about 12 parameters were considered relevant for estimating the benefit of water injection, and these were generally focused around in-place volumes and reservoir rock and fluid properties.

The overall completeness of the database was about 40% (with the permeability, for example, at about 5% and the initial reservoir pressure at about 87%), and dataset consistency was only 6% over all reservoirs. A successful ranking exercise would have not been possible under the initial condition of the database.

Back-population of Missing Data

To correlate as many characteristics (parameters) of a given reservoir and, consequently, increase the quality and confidence of the conclusions for reservoir classification, the data gaps must be filled. The gap-filling methodology applied here involves multidimensional cross-correlation using SOMs.

The benefit of using this methodology lies in the multi-variant approach, which is much stronger and less error-prone than non-linear trending methodologies usually applied for these purposes (Zangl 2003). Provided the multi-dimensional relationship is inherent in the data and the quality of the data has been increased through outlier removal, the SOM is able to estimate a value for a missing data point by learning the relationships of the parameters amongst each other.

The SOM models in this case are used as a regression tool to compute missing values based on the available values of a certain measurement and based on the identified correlations among the parameters. The SOM hereby computes a model that describes the measurements in a data cloud in an optimal way. For this purpose it creates a smaller, virtual data cloud with the same dimensions (measurement parameters) as the observations and tries to fit this virtual data cloud to the observed data cloud by placing the virtual nodes as close as possible to the measured nodes. The measure of proximity hereby is the Euclidean distance

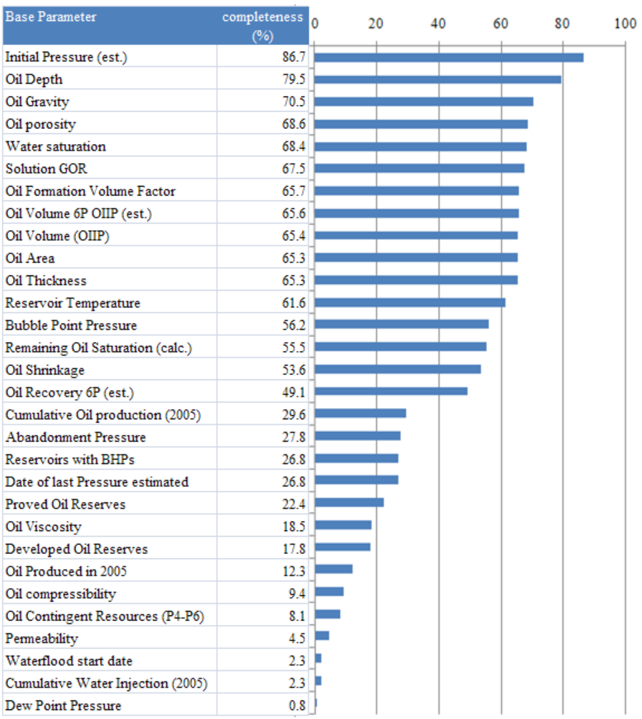

FIG. 2 EXAMPLES OF DATA AND THEIR COMPLETENESS OVER THE ENTIRE RESERVOIR PORTFOLIO

(Hair, 1998). An optimization algorithm distributes the observation nodes in the multi-dimensional space, so that the sum of Euclidean distances to the measurement nodes is minimized; which corresponds to the best fit of virtual to observation cloud. By matching the virtual with the observed data cloud, each measurement is associated with a virtual node, where many observation nodes can share a common observation node. After the analysis of global and local errors and considering them acceptable, the matched virtual data cloud generated by the SOM is a reasonably valid virtual representation of the observation cloud and can be used to predict missing values of incomplete measurements. In order to achieve this, the incomplete measurement is placed into the virtual data cloud as close as possible to the virtual node that is the most likely to be similar to the incomplete measurement (according to the Euclidean distance calculated from the available values). It can now reasonably be assumed, that the incomplete measurement is similar to the virtual node that has been assigned to; hence it can be derived that the missing values in the measurement are equal to the values of the same parameters of the virtual node.

In the presented workflow, the back population workflow is used in a slightly advanced way, by not just applying the deterministic values of the closest virtual node to the gaps, but by looking at all adjacent, also similar nodes (same cluster), and back-populate the missing value as a stochastic representation through a normally distributed probability function defined by the mean and standard deviation of the obtained values. This rigorous consideration of measurement and model uncertainties helps to improve the result of the investigation and increases the unbiased character of this analysis. The limitations of this approach is that the back-population procedure, as applied here, can only be used with a reasonable degree of accuracy when the available values of an incomplete measurements are sufficient to confidently place them in the virtual data cloud. If that is the case, the overall accuracy of the model is not impaired by introducing the incomplete measurements.

Completeness and Consistency Check

The methodologies applied in the back-population process require the datasets to adhere to a certain consistency, which has a direct impact on the degree of completeness. Measurement gaps in datasets can be filled using regression approaches as described in this paper. However, the consistency with the natural rules and concepts of a petroleum reservoir has to be maintained at all times in the process to guarantee the reliability of the results. Therefore, only those datasets can be back-populated with a sufficiently high degree of certainty, which have enough measurements available (hence only few degrees of freedom of the back-population approach) and therefore allowing to obtain a more precise estimate for the missing value(s). Analyzing the completeness aids in the assessment of those parameters that can be used for further analysis and those that need be back-populated to be included in the workflow.

Although the initial reservoir pressure is the most complete of all available reservoir parameters, for more than 15% of the reservoirs the (initial) pressure is unknown. In, at least, 90% of the reservoirs some factors like average permeability and oil compressibility are unknown. FIG. 2 shows the completeness of zero-dimensional data from Chevron Nigeria Ltd.'s entire reservoir portfolio and illustrates the variability in the completeness of reservoir parameters available for study.

Parameters like permeability, compressibility, and oil viscosity show the lowest degree of completeness, thus representing the limiting parameters for the reservoir classification and the back-population process. In the following combinatorial analysis, the

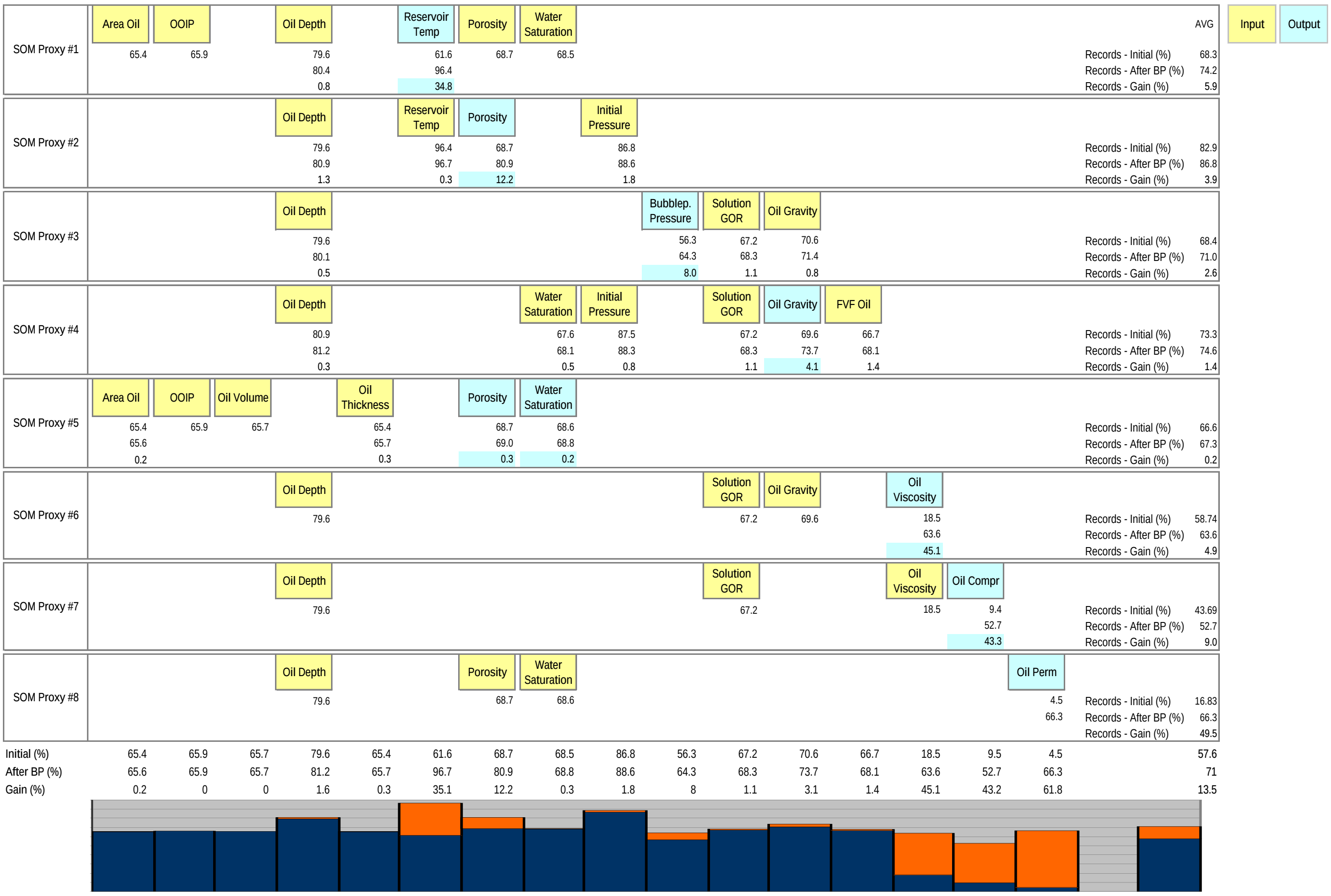

FIG. 3 STEP-WISE SOMS FOR BACK-POPULATION WITH THE COMPLETENESS LEVEL AT THE BOTTOM (BACK-POPULATED DATA ARE ORANGE)

combinations of parameters are tested with regards to the number of complete patterns they can yield using back-population to estimate the missing values, while still obeying the rules of consistency.

As an example, varying combinations of the identified limiting parameters with a maximum number of six parameters increase the number of complete patterns from 69 to 1,110 (4 to 65%), depending on the original completeness of the parameters. Obviously, those parameters with a higher completeness, as initial pressure estimated (completeness of 86.7%) or oil depth (79.5%), yield a substantially higher number of complete patterns than combinations with oil compressibility (9.4%) or oil viscosity (18.5%).

The consistency analysis thus guides the back-population process in the setup of proxy models, because they identify those combinations of parameters that yield the highest overall completeness of the dataset.

SOM Proxies

The combinatorial analysis has yielded eight combinations of parameters (minimum of four, maximum of six parameters) which are used as SOM proxy models to consistently back-populate individual parameters (Kohonen, 1990, 1997, Hair, 1998). FIG. 3 shows the proxy models. Each relates a set of input parameters (in yellow) to one—or in one specific case, two—output parameters (in light blue), where the output presents the estimation of the SOM back-population process.

In the case of the limiting parameters permeability, compressibility, and oil viscosity, it can be seen that the gain is the largest (between 43 and 62%), thus contributing to an overall gain of 13.5% by combination of 16 parameters.

This gain might not seem substantial but it unlocks a much greater number of patterns (1,120), combined with a larger number of parameters (12), thus increasing the quality of the subsequent reservoir classification.

Blind Test and Validation

To prevent SOM proxy outcomes from being influenced by observer bias or to verify the proxy models on their stability and predictability a blind test

is performed after each back-population. The blind test is used to identify the error that is induced during the back-population process. This error is inversely proportional to the quality of the SOM proxy and is therefore directly reflected in the overall error of the back-populated dataset.

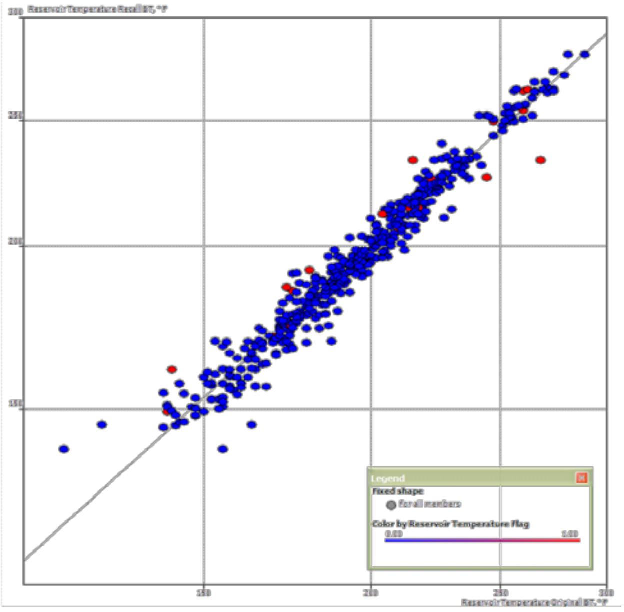

FIG. 4 CROSSPLOT OF ORIGINAL VERSUS RECALL OF RESERVOIR TEMPERATURE FOR BLIND TEST OF SOM PROXY #1 (RMS=0.965) WITH TABLE DEPICTING EXAMPLES OF RESERVOIR MEMBERS WITH THEIR RECALL ERROR

The blind test is performed by removing 5% of all complete patterns. A SOM is subsequently trained on the remaining patterns, after which a recalculation is performed to back-populate the removed values. By comparison of the back-populated values with the removed values the error should not exceed 5% (see FIG. 4) as this would be an unsuitable SOM proxy and not acceptable for back-population (Zangl 2003). Additionally, the values for the blind test are evenly distributed across the entire parameter range to assess the validity over the entire SOM proxy space / range.

SOM Proxy Quality and Completeness Ratio

The previously defined blind test error is used to define the error ranges for each individual data member—regardless if observed or SOM proxy back-populated data. This error is considered for each value in the database to contribute to the probabilistic character of the data members and is referred to as the SOM quality. The error is used to weight the standard deviation of the data range for each cluster.

Additionally to the SOM quality, the completeness ratio is introduced. The completeness ratio is a measure of the degree of back-population carried out for an individual parameter. It is derived by calculating the ratio of the initial to the final number of records. As described earlier, permeability, compressibility, and viscosity show the lowest values for completeness ratio, as these parameters exhibit the lowest completeness. The SOM quality ranges from the blind tests for the individual parameters show a distribution from 0.47 to 6.39%, which can be attributed to the removal of outliers in the original dataset.

Reservoir classification

It is apparent that the reconstructed or in fact any database in its entirety cannot be used for an effective (i.e., rapid) screening exercise that uses a sophisticated algorithm and derives a valid objective function for all data members at the same time. The screening algorithm works most accurately, when it is applied to similar data members distinguishing between the applied processes where, for example, in this case different reservoir mechanisms prevail. For example, it can be assumed that the screening algorithm for identifying the benefits of water injection will work differently for oil reservoirs with and without gas caps. FIG. 5 depicts the SOM clustering of all reservoirs over 12 parameters. The seventh SOM plot for example, which shows the gas cap factor m, groups gas-cap reservoirs in separate clusters like “islands” in the blue, non-gas-cap “sea.” A screening algorithm dedicated to the clusters rather than the entire database will yield more accurate results.

SOM clustering has significantly increased the focus on the data amount from over 1500 individual reservoirs to 17 groups of reservoirs with comparable properties and possibly with similar behavior. Each of these 17 groups is clearly defined by particular features that vary significantly from one group to the other (e.g. significantly different viscosities, porosities, etc.); but vary only slightly for the reservoirs within a particular group (Kohonen, 1990, 1997, Hair, 1998). FIG. 6 shows the property distribution and the mean value of four example properties for each of the identified clusters.

Conversion to a Probabilistic Database

Each cluster can be statistically analyzed for its property distributions assuming a normally distributed set of data to derive mean values and standard deviations. FIG. 7 shows the statistical indicators of the various properties for some clusters.

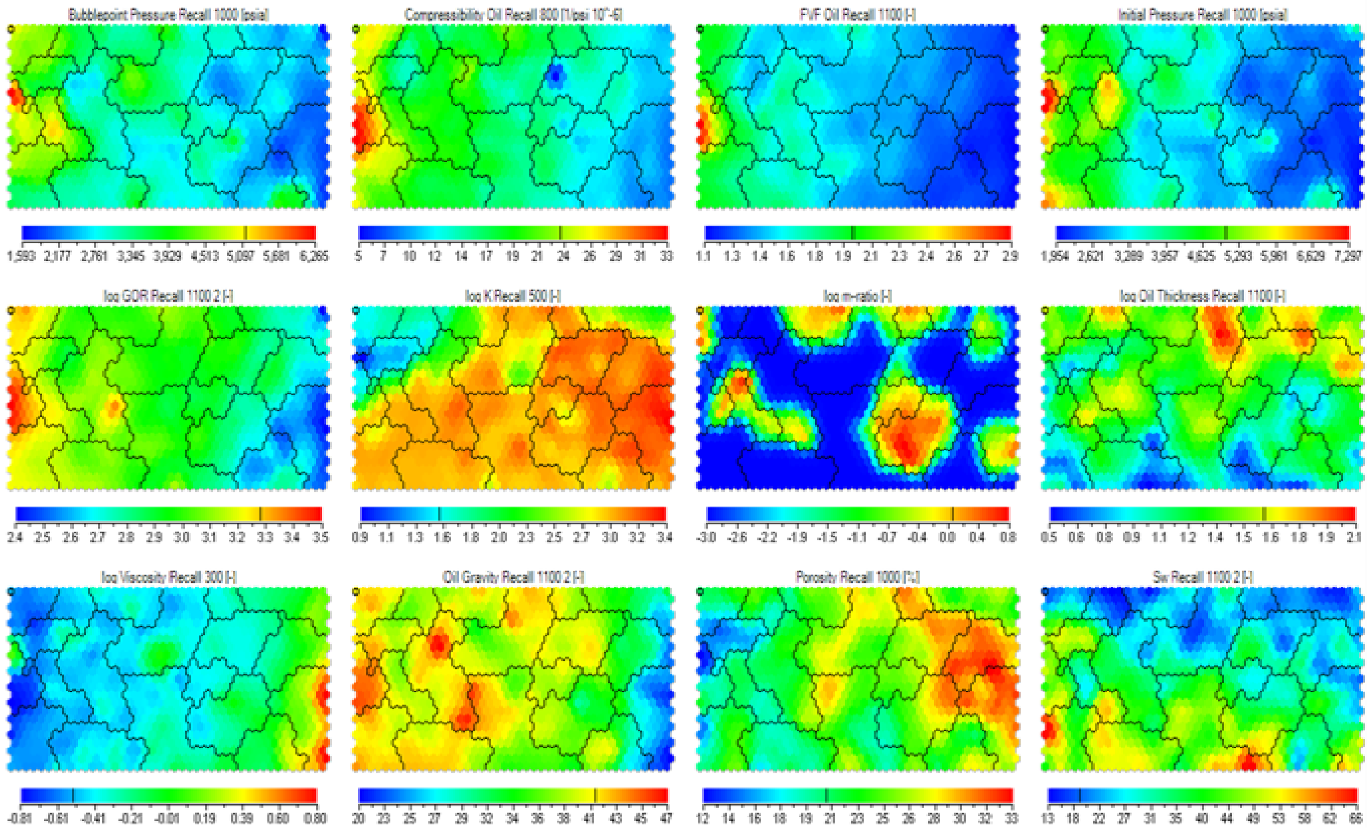

FIG. 5 SOM REALIZATION FOR EACH PARAMETER; BLACK LINES DELIMIT THE VARIOUS CLUSTERS

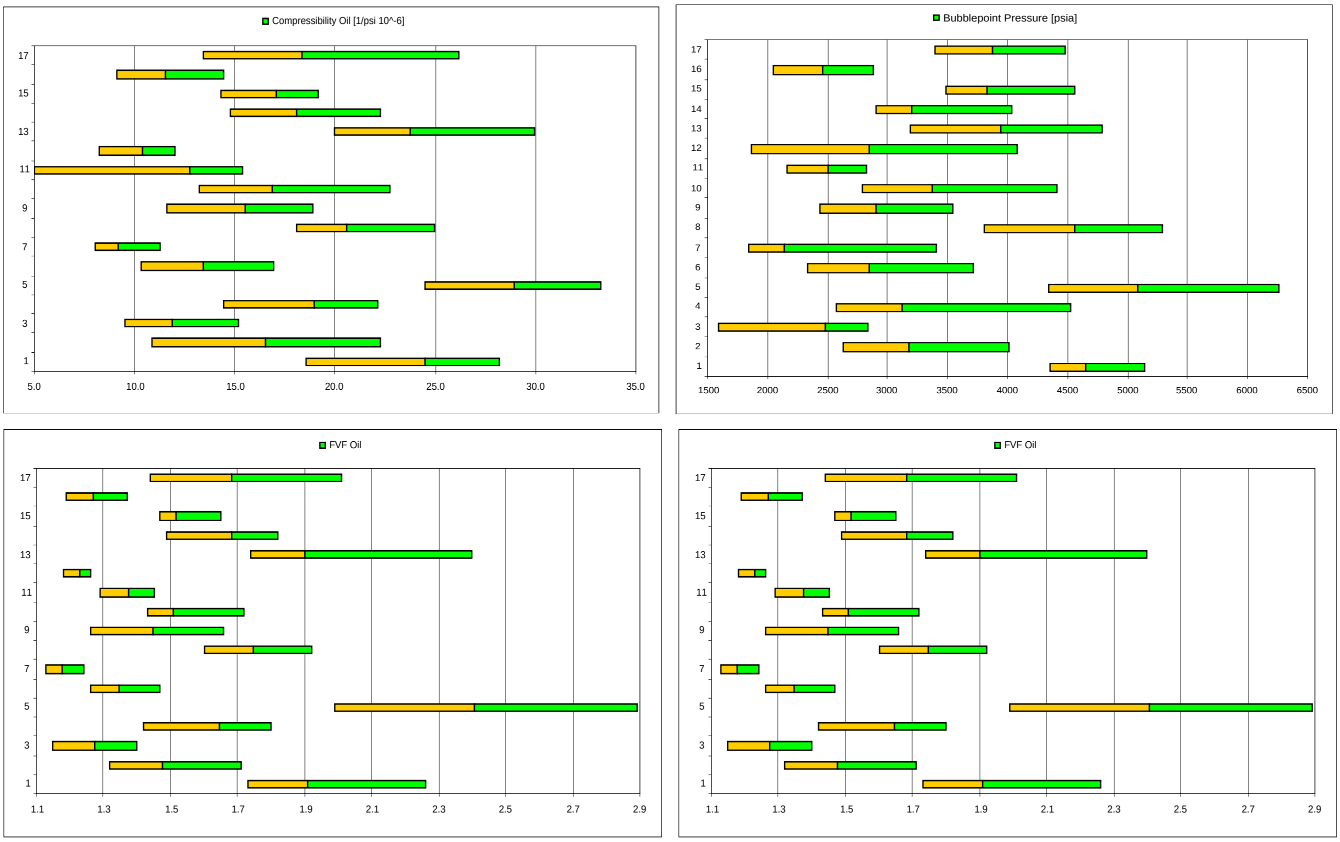

FIG. 6 PVT PROPERTY DISTRIBUTION WITH MINIMUM, MEDIAN AND MAXIMUM VALUES FOR THE 17 CLUSTERS

PVT stands for the "pressure", "volume", "temperature" relationship. To avoid physical impossibility or incorrect values during the screening exercise, minima and maxima – the lowest and highest values observed in a particular cluster – must delimit the bell-shaped distributions.

The cluster distributions for a parameter are applied to the individual data members by overlaying the standard deviation of the cluster onto the database value. The SOM proxy error from the blind test is used to modify the standard deviation. Each individual data member contains then a mean value, an individual standard deviation, and the physical upper and lower limits from the cluster.

The Screening Engine

For the purpose of this paper, the definition of a screening engine is an algorithm that captures a process or method to arrive from the input signal to the output signal. The screening engine could capture any kind of complexity of the process. A mathematical operation on the database would be a fairly basic engine to derive an objective function for screening, but the engine could also be as complex as deriving the possible oil recovery and production rate of reservoirs. Moreover, since the database is probabilistic, the screening engine must run in a Monte-Carlo-type simulation to construct the output distribution. Considering the extreme amount of calculation necessary to define the output, numerical screening engines—as in this case for the recovery definition—are impractical. However, proxy models that capture the input–output relationship of the objective function are feasible.

The challenge for a stochastic computation like the one described here is to compute complex numerical reservoir simulation models in a fraction of time of a conventional numerical engine in order to allow for many different realizations in a reasonable time. Reservoir simulation is usually based on the finite difference - finite volume approach to efficiently handle the multi-phase flow in porous media using tens to hundreds of thousands grid blocks. The screening engine hence needs to take advantage of a suitable proxy that can execute fast enough to allow for a Monte Carlo Analysis with several thousand runs for over 1,500 reservoirs. The proxy selected in the presented work is based on a surrogate reservoir model. Surrogate reservoir models yield similar results as an actual numerical simulation model of a reservoir while running in a fraction of a second (Mohagegh et al. 2006). In contrast to a reservoir simulation engine, which takes into account the laws of physics and fluid flow in porous media, a surrogate model as a proxy model is typically merely "calibrated" on a small sample of input-output data sets from previous simulation runs. The sample datasets should ideally be very small while still containing enough scenarios to cover the whole space of possible input and output as described in several experimental design (ED) strategies (Box, 1960; Damsleth et al. 1991; Dejean and Blanc 1999). After being calibrated on these samples the SRM based proxy has the capability of mimicking the simulation model on the full range even though it does not have to go through the complex computation of a numerical engine. Hence, the execution time of a surrogate model is typically in the range of a fraction of a second and it therefore can be considered a very suitable approach to run multiple

Cluster number		p_b (psi)	c_o (1/psi 10^5)	B_o (rbl/stb)	p_i (psi)	Rs (scf/stb)	K (mD)	m (-)	Δz_o (ft)	μ_o (cP)	ρ_o (°API)	ϕ (%)	S_w (%)
1	Min	4357	18.5	1.73	4468	1259	22.4	0.0	15	0.21	37.58	15.7	17.9
	Max	5145	28.2	2.26	5319	1995	81.3	2.1	40	0.30	44.43	23.9	42.9
	Mean	4650	24.5	1.91	4815	1586	42.6	0.4	26	0.26	40.87	20.4	26.1
	Std Dev.	226	2.7	0.10	246	197	13.9	0.6	7	0.07	1.41	2.6	8.2
2	Min	2632	10.9	1.32	2651	575	46.8	0.0	13	0.30	36.21	19.8	14.4
	Max	4016	22.3	1.71	3901	1202	1479.1	2.5	47	0.68	42.16	31.0	44.8
	Mean	3180	16.6	1.48	3234	842	729.7	0.8	26	0.42	39.10	25.6	25.0
	Std Dev.	298	2.5	0.07	290	121	448.1	0.6	7	0.14	1.37	2.9	6.0
3	Min	1593	9.5	1.15	2453	224	125.9	0.0	18	0.54	24.01	22.6	15.1
	Max	2840	15.2	1.40	3703	759	1047.1	0.8	72	1.62	37.26	27.2	23.6
	Mean	2479	11.9	1.27	2679	517	383.5	0.1	38	0.97	31.20	25.0	19.8
	Std Dev.	257	1.8	0.06	280	131	206.5	0.2	13	0.54	4.20	1.4	2.6

FIG. 7 DERIVED PROPERTY DISTRIBUTION WITH LIMITS FOR THE SOM CLUSTERS USED TO CONSTRUCT THE STOCHASTIC PROJECT DATABASE (CLUSTERS 1 TO 3)

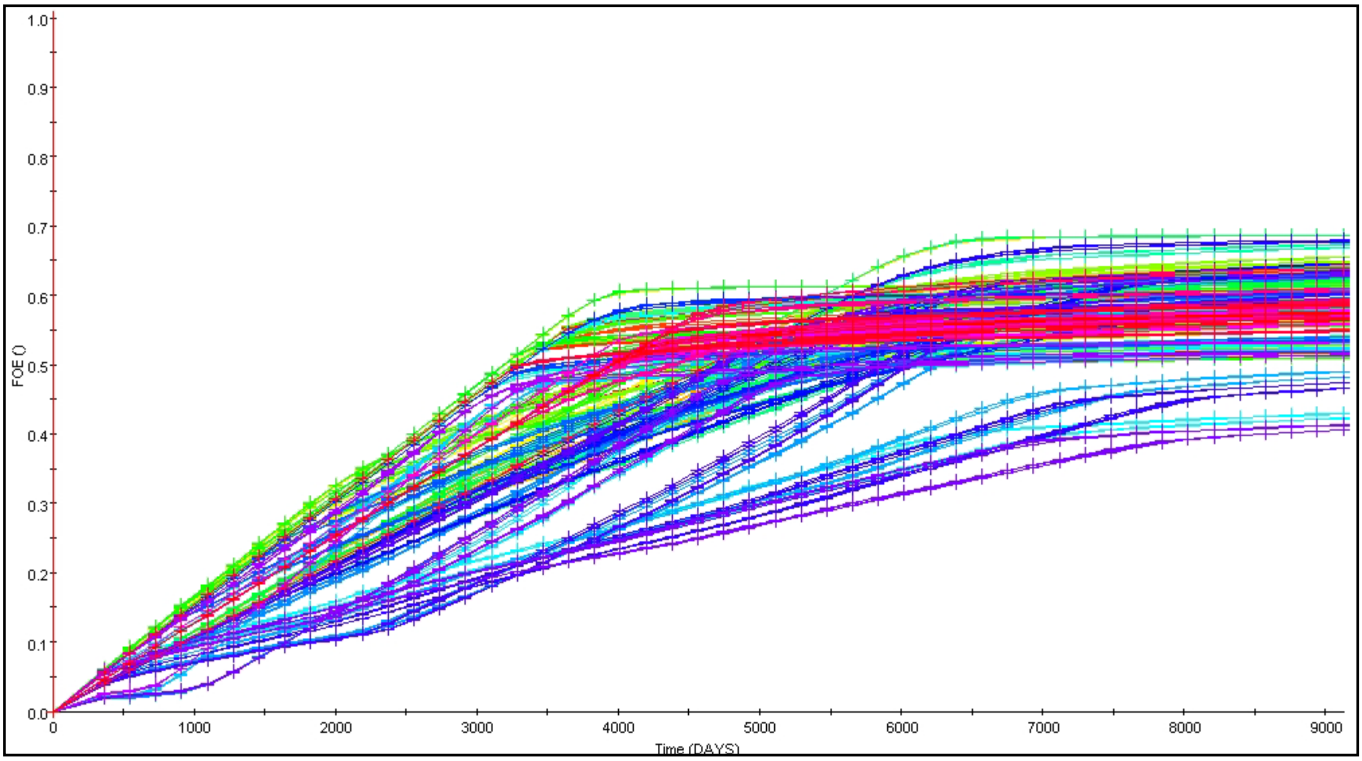

FIG. 8 MULTI-RESPONSE PLOT FOR THE OIL RECOVERY OF CLUSTER 4 WITH WATER INJECTION

thousand reservoir simulation runs in a stochastic layout.

The aim of the SRM in this work is to approximate a process by a simple regression model that fits the true response with a sufficient degree of accuracy and which will hence act as the quick response surface. The response surface approximates the process by regressing on the executed experiments which were executed using ED. A large variety of proxy models exist in what can train on the history of an input-output relationship and predict for unknown output responses, or the output response of an objective function on input data alone, or use a combination of both (Zangl et al. 2006). It must be noted that the response surface based on a proxy model is only an approximation and is not as accurate as the process itself—but, neither is the data members in a probabilistic database. It can be assumed that the simulation of the proxy model over the entire input spectrum will derive an output distribution that eventually covers all inherent errors and uncertainties. Moreover, it is the speed and not the exact solution that is required for the screening exercise.

Recovery Proxy

The most important objective function to address the impact of the waterflood on a reservoir is the recovery factor. The difference between natural depletion and water injection can be determined through the recovery factor to allow a qualitative statement on the benefits of secondary recoveries for individual reservoirs.

A simple two-dimensional, slanted numerical model has been constructed that represents a cross-section through a generic-type reservoir. A production well is located in the attic in the case of an oil reservoir and half-way in-between the contacts in a gas cap reservoir. One injection well is located directly in the aquifer to support for the waterflood experiments. The models are populated with uncertain rock and fluid properties defined from the clustering exercise. Inherent uncertainties such as aquifer strength and heterogeneity are also included.

ED is used to effectively simulate all possible combinations of the uncertainty parameters. The combination of stochastic and deterministic uncertainties requires about 600 experiments to be simulated for each recovery strategy and each cluster (FIG. 8) amounting to about 20,000 simulation runs to construct the necessary output space for the RSM.

The RSMs have been used on the database to define the benefits of waterflooding according to the cluster properties and their associated uncertainties. A Monte-Carlo simulation is performed on each data member

considering its distribution from the probabilistic database as constructed with the help of the clusters. The output distribution—the difference between the recovery with and without water injection—is a qualitative statement on the benefits of waterflooding. The output distribution is then discretized for the use in the BBN screening process.

Candidate Screening

The candidate screening is performed using an expert system based on a BBN. The BBN is applied to describe and reconstruct a complex decision process involving multiple parameters, adding the notion of uncertainty (Neapolitan 2004). The various input parameters in a BBN can either be conditionally independent—not having any influence on each other—or conditionally dependent. In the latter case, prior knowledge of the dependency of the various parameters must be quantified and entered as a conditional probability relation in the BBN; this is done either by using a Bayesian learning approach or manually through an expert (Mitchell 1997; Korb and Nicholson 2004). In this work, a BBN was set up purely by experts to consistently reproduce their reasoning process on a large number of samples (reservoirs), considering the various aspects of their decision such as economic, logistic, and reservoir considerations. The outcome is a score between 0 and 100 that describes the reservoir's applicability for waterflood recovery.

The input parameters in a BBN can either be continuously measured variables or discrete variables. In the given project, some of the input variables are entered considering uncertainty in the measurements, computation, or in the reasoning process, such as the recovery factor as discussed in the previous section. By discretizing the stochastic input into a limited number of categories called "states," the stochastic properties of the input can be fully considered while maintaining a computationally cheap BBN. The result of the BBN is a decision score, which represents the likelihood that a given reservoir is a good candidate for secondary recovery, fully considering the inherent uncertainty of the variable measurements and computations as well as the expert's decision process. In order to compute the score, the BBN processes the input distributions in the various nodes and their conditional interaction according to the expert logic about conditional probability applying Bayes' theorem. Prior probabilities (expert knowledge) are multiplied with the input probabilities (observations or computations from proxy model) and normalized to obtain probability values from zero to one, which is from impossible to definite outcome given by the observation and expert knowledge, respectively.

There are three different decision criteria leading to the final decision on whether a reservoir is a viable candidate for a waterflood operation or not. The three reasoning trains are conditionally independent and hence information from one process does not influence any other decision criteria, which is why experts from various disciplines can contribute to the reasoning system and benefit from a holistic expert system. A graphical representation of the BBN is given in FIG. 9. In the depiction, the gray boxes denote input variables, the white boxes decision points, and the arrows the parameter dependencies (Jensen 2001). The criteria are

1. ***Economic viability***: This decision criterion takes into account the estimated recoverable hydrocarbon reserves that can be exploited using the same infrastructure (i.e., stacked reservoirs), the possible proximity to waterflooding infrastructure (e.g. from other fields), logistical issues (onshore, offshore), and the operational security.
2. ***Physical viability***: The physical viability criterion looks at the suitability of a reservoir for a waterflood regarding its reservoir and aquifer properties.
3. ***Potential delta recovery***: The third reasoning process processes the outcomes from the calculation of the proxy models. The objective is to quantitatively describe the potential additional recovery that can be realized by secondary recovery.

Economic Viability

An important aspect of the ranking procedure is the economic viability of a potential secondary recovery project. In contrast to other technical reasoning systems that focus on incremental recovery and/or incremental net-present-value (NPV), the given expert system takes into account factors such as the proximity to other waterflood installations of existing waterflood operations in other fields, the logistics, and the operational aspects.

The stacked oil-initially-in-place (OIIP) in combination with the possible proximity to other waterflood installations gives the initial estimate of whether a

given reservoir is a good candidate to initiate waterflood operations. The higher the OIIP, the less important is the proximity to other waterflood infrastructure as a high OIIP would certainly justify the investments in necessary infrastructure. Once the volumetric and infrastructural decision has been made, the expert system investigates the operational security aspect as well as the geographical logistics. Some of the fields are offshore or in swamp areas, which—even though volumetrically the field might be of significant value—downgrades the score of this particular field. Also, security concerns are addressed, which is why the expert system takes into account whether the given field is in an area that can be considered as a well-controlled and high-security area. If this were not the case, a field would be ranked lower in the candidate ranking process even though many other factors might suggest incremental benefits (or value).

Physical Viability

Based on available information or estimations of reservoir and aquifer properties, the drive energy of the candidate reservoir is assessed. Reservoirs with a high initial reservoir pressure and a weak aquifer are preferred as these reservoirs generally show the most benefits from waterflood operations.

Production enhancement potential as well as displacement and sweep considerations are incorporated in the hydrocarbon delivery potential decision. The expert system favors reservoirs with a thick oil rim and hence high production enhancement potential.

Reservoir Ranking

The final decision node combines the finding from the economic viability decision, with the physical viability decision, and the determined delta recovery and integrates them into a final conclusion.

By introducing the three independent decision processes, with independent inputs, the formulation and quantification of the reasoning logic for the final decision becomes less complex. Each of the decision process branches can be considered individually and hence not all the inputs are fed into the same decision logic. The three independent decision process branches require a much less complex reasoning logic entered by the expert, compared to a single decision logic description that considers every parameter at the same time. The branches are processed parallelly and separately; only in the last decision, the score, is the three branches combined to a final decision. This approach significantly facilitates the expert team that sets up the reasoning logic because the number of possible combinations of input variable states is reduced significantly.

The final decision is represented as a score between 0 and 100 points, with 0 points signifying a poor candidate and 100 points identifying a very promising and suitable candidate for waterflooding. The influence of the various process trains is weighted differently by the expert team according to the importance of each train in the decision process. Economic viability has the biggest impact, because a field with good reservoir and fluid properties and a good delta recovery is of limited interest if it is in a low-security area and/or in a swamp area. Physical viability and delta recovery are almost equally weighted; and the former has a slightly higher impact on the results of the final decision to compensate for potential uncertainties arising from the proxy model calculation.

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Each candidate reservoir is scored according to this reasoning system. The results are sorted according to the likelihood whether a particular candidate is a good candidate for waterflood operations (represented by the score). The results from the individual decision processes are stored along with the final result for every candidate reservoir to be able to investigate the reasons for a particular final score and to possibly manually adjust individual scores (e.g., a bad score might be due to a lack of available waterflood infrastructure; however, good reservoir properties and high estimated incremental recovery could make the reservoir still a good candidate for a waterflood).

The final ranking is then checked by the entire integrated team to agree on a final short list of candidate reservoirs for secondary recovery.

Validation of Reservoir Ranking

In an effort to understand the validity of the results of the stochastic screening exercise, the ranked list of candidate reservoirs was compared to a previously generated ranking list from standard deterministic screening exercises based on calculated key performance indicators (KPIs) and subjective estimations of reservoir behaviors from the data at hand. This screening effort used the identified characteristics of successful waterflood reservoirs as search criteria to recognize candidate reservoirs for new waterfloods.

Although both methods used the same input parameters in their objective function, the main difference is in the introduction of the confidence in the data and the stochastic character of the database. This allows ranking technical key indicators without bias, whereas deterministic screening and expert-guided rankings are subjective. The two screening efforts proved to be complementary, and a composite list of candidate reservoirs was identified for the next phase of evaluation. Candidate reservoirs identified in the Phase 1 screenings were validated in workshops with each of the asset teams. Overall, the Phase 1 screening results aligned well with asset team perceptions of additional waterflood potential. Asset team feedback recommended only 9 reservoirs to be dropped away and 4 reservoirs to be added to the original candidate list of 104 reservoirs, resulting in a final list of 99 waterflood candidate reservoirs.

Additionally, the effort of benchmarking the resulting reservoirs from the stochastic screening with the reservoirs currently under waterflood proved to be consistent, thus underlining the applied methodology. Also, before the study was conducted, only 25 reservoirs in the reserve system were recognized as waterflood candidates with considerable secondary recovery potential, indicating there should be significant potential for resource and reserve additions.

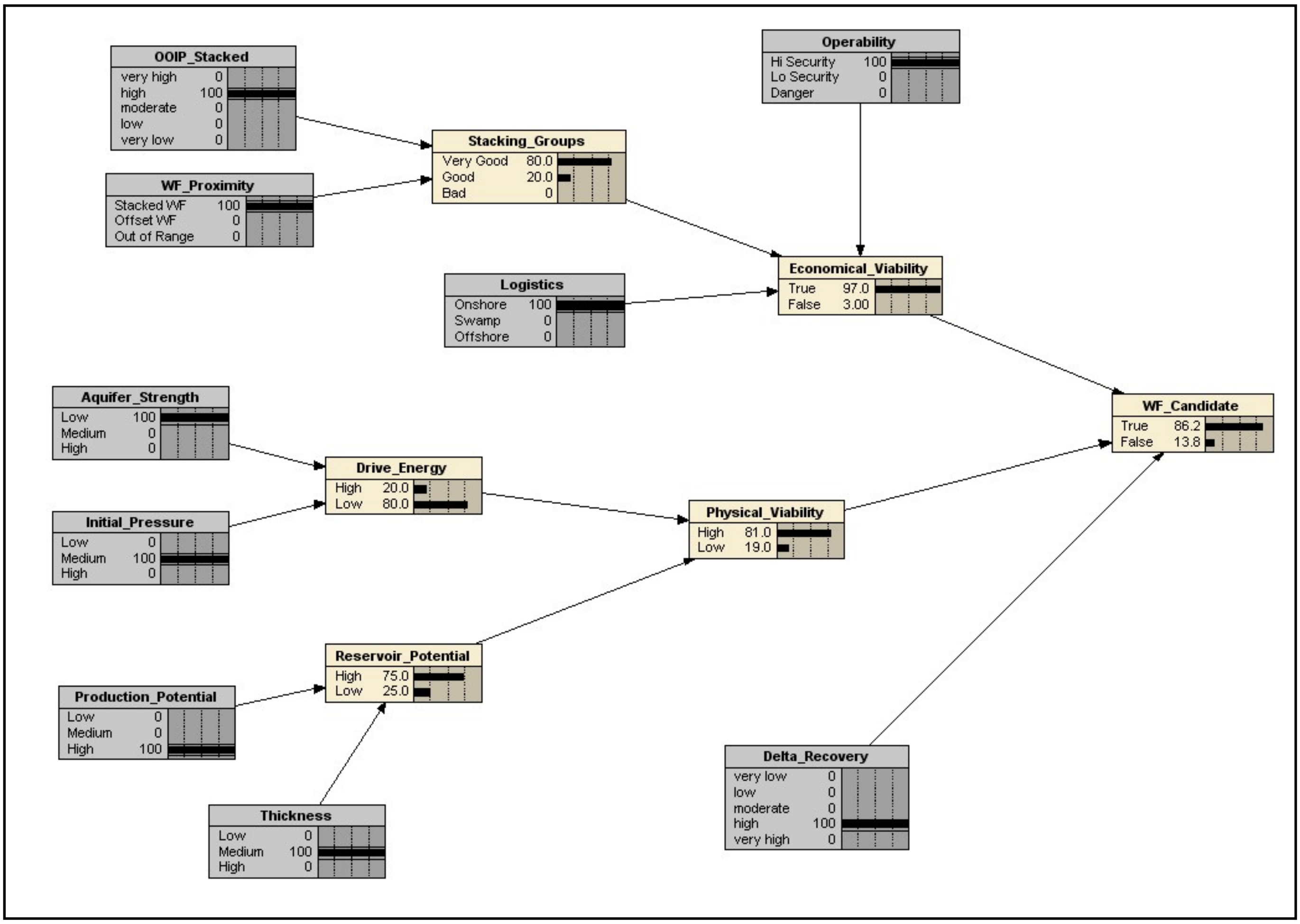

FIG. 9 THE REASONING TRAINS, STATES AND PROXIES, AS THE BASIS FOR THE BBN TO SCREEN RESERVOIR CANDIDATES FOR WATERFLOOD IMPLEMENTATION

Conclusions

To the authors' knowledge, this is the first attempt to create a probabilistic database using a stochastic, SOM-based back-population algorithm. Furthermore, it has been shown that SOMs can be used to describe the confidence in the existing and reconstructed data for input into a probabilistic database without bias and based only on statistical analysis of the data members. A screening engine was constructed—the recovery proxy—that used the database to define key indicators for input into a BBN-based ranking exercise. Although the screening process itself contains a significant number of procedures and algorithms, once they are identified for a particular problem, the ranking can be applied rapidly to similar datasets. In fact, the engine—the recovery proxy in this case—can be changed to any querying proxy model algorithm allowing the application of this workflow to any KPI-based screening exercise regardless of the complexity of the process the engine describes.

Although the database is defined without bias, and the workflow is highly computational and intends to reduce human interaction with the screening engine, the screening process achieves the best results with expert knowledge systems such as the BBN. In fact, the BBN offers a systematic approach to screen for technical and nontechnical (security, for example) aspects at the same time in cases in which perception and judgment are required for the ranking exercise.

The benchmarking of this case study with traditional, deterministic methods reveals similar ranking results, but results are achieved more efficiently and faster using the stochastic method. The acceleration comes from both the probabilistic data handling and the screening engine. Rather than exact values, the confidence levels of data are enough to run database algorithms and compute the objective function for the screening exercise. Time-consuming preparations of a deterministic database are therefore not necessary.

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